McKinsey & Company

Retail Analytics

# Analytical assortment optimization

Maximizing assortment profitability at the push of a button.

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# Executive summary

An ever-growing number of SKUs to choose from, limited shelf space, heterogeneous store characteristics, and supply chain complexity put increasing pressure on retailers to get assortment right.

Assortment management has evolved significantly beyond simple performance metrics such as total sales or rotation numbers. In fact, big data and advanced analytics now enable comprehensive analyses of customer behavior at the push of a button. An example of this is McKinsey's walk rate metric, which quantifies a product's uniqueness by predicting the share of product sales that transfer to other products in the category when the product is delisted and the share that would "walk away" and be lost sales for the retailer. Retailers that effectively apply the full set of assortment analytics can enjoy increased gross margins of up to four percentage points higher.

Starting the analytical assortment optimization journey is straightforward. A four- to six-week pilot can allow a retailer to quantify the value of its assortment lever based on a few select categories and generate actionable insights for immediate implementation.

# 1 Assortment optimization's growing importance and power in overall retail performance

## Securing value through systematic assortment optimization in an increasingly complex and space-constrained retail landscape

Finding and maintaining the optimal assortment of products to sell in stores has always been at the core of a retailer's commercial activity. Retailers who get the assortment right enjoy more sales, higher gross margins, leaner operations, and most importantly, more loyal customers.

Recent developments in the market make assortment optimization more important than ever:

**A growing number of SKUs:** Large brands are continuously innovating and increasing the number of their SKUs. While small brands may offer fewer individual SKUs, the number of small brands is rapidly increasing. Finally, the number and share of private-label products is also growing at a brisk pace.

**Limited physical shelf space:** As the number of products is growing, shelf space is not. Opportunities to expand or reallocate shelf space between sections is limited to nonexistent. And many new stores are opening in space-constrained, inner-city markets, exacerbating shelf space challenges.

**Growing supply chain complexity:** Even though the number of SKUs continues to grow, the supply chain becomes increasingly complex, compounding the need for thorough reviews of what should be listed or removed from the assortment.

**The "agony of choice" on the endless virtual shelves:** Even in e-commerce, where there is presumably infinite shelf space, retailers must manage assortment to hold customers' attention and control the costs of inventory and logistics.

**Location-specific dynamics:** Diversity is growing across each retailer's stores, with increasing variation in size and format. Location factors, such as traffic connection and neighborhood sociodemographics, mean that not all SKUs and categories perform similarly across all stores. Assortment must therefore be optimized to the specifics of each store location. This optimization typically involves macrospace allocation (how much space to dedicate to a specific category in each individual store) and localization (finding the optimal SKU mix for each store).

Developing a more analytical assortment management process pays off, as the insights gained can lead to improvements across several areas. These improvements can significantly enhance financial performance (Exhibit 1):

— *Systematic delisting.* The ability to steer customers toward higher-margin products can contribute up to 0.5 of a percentage point to gross margins. Work with leading international retail players shows that a significant reduction in SKUs can be achieved without endangering sales levels (see sidebar "Less is more: Assortment optimization in e-grocery").

Exhibit 1

## Effective assortment management can significantly improve financial performance.

**Expected annual contribution across individual value levers**

| | | | |
|---|---|---|---|
| | **Systematic delisting** | Profit margin improvement from better product mix | Up to 0.5 pp[1] of margin |
| | **Strategic listing** | Coverage of previously neglected or underrepresented customer needs | 2–4% revenue growth |
| | **Simplified supply chain** | Lower operating cost in supply chain, branch operation, and product development[2] | Up to 0.5 pp of margin |
| | **Improved procurement conditions** | Improved negotiation leverage due to better understanding of supplier importance | 1–3% of procurement costs |
| **Additional value increase due to working capital reduction (one-time cash release and annual reduced capital cost)** | | | |

[1] Percentage point.
[2] If applicable.

— *Revenue increase through strategic listing.* Retailers could realize an additional 2 to 4 percent increase in sales through a more customer-centric product portfolio.

— *Simplified supply chain.* A margin improvement of up to 0.5 of a percentage point can come from a reduction of costs related to operations and supply chain, as well as—in situations where there is a high share of private-label products—product development.

— *Improved procurement conditions.* Knowing a product's uniqueness—the likelihood that a customer will replace it with another—provides retailers with important information when deciding whether to delist a product or an entire brand. Knowing not to be reliant on a particular product or brand, retailers will have more bargaining power with suppliers regarding their terms. This advantage can lower procurement costs by up to 3 percent.

## Capturing value from assortment optimization through advanced analytics

Significant improvement in financial performance and customer experience is possible through assortment optimization, but it requires a deep understanding of assortment performance beyond the superficial. For instance, strategic listing entails more than introducing every "hot" item that comes to market. Similarly, smart delisting is more than cutting slow-moving items. Indeed, determining which SKUs to cut to make space for new ones requires not just a detailed, store-level look at financial performance but a deep understanding of customer purchasing behavior as well. This means, for example, quantifying how unique an SKU is for the customer or identifying the customer needs that must be covered by the selection of products in the category.

## Less is more: Assortment optimization in e-grocery

**McKinsey worked with** an e-grocery retailer to apply an analytics-based assortment optimization process that would create benefits both directly (improving gross margins) and indirectly (reducing warehouse complexity).

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We introduced a delisting approach based on key performance indicators (KPIs). First, category managers used customer decision trees to more fully understand their categories. Category managers particularly embraced the "uniqueness" KPI, which helped them understand the incremental contribution each SKU made in its category. Over the course of the pilot, the team used deep customer insights such as category–specific price sensitivities and cross-selling potential to inform delisting decisions. We also trained all category managers in KPI-driven assortment optimization.

Assortment optimization resulted in a 36 percent reduction in the number of SKUs and projected growth of 1–2 percent in both sales and gross margins.

The analytical tools that can help category managers gain this critical level of insight have been around for a while, but the way they have been deployed constrained their impact. Specifically, the advanced analytics used in assortment decision making have mostly been in the hands of dedicated technical departments within the retailer or even with specialized external providers. This distance between the analytical and overtly business-focused parts of the company means that most retailers have not been able to capture a significant share of the potential value.

Today, big data and advanced analytics applications are increasingly accessible to nontechnical users. With analytics-enabled insights in the hands of category and commercial managers, retailers can make informed assortment decisions that bring real value.

# 2 Navigating the assortment optimization cycle

**For some, assortment management** is still synonymous with basic routines such as listing new products from large brands and delisting the most slow-moving items in the category. However, world-class retailers with exceptional assortment management skills conduct ongoing assortment optimization with a more nuanced view. The continuous process involves listing and delisting from the list of all SKUs which are listed in at least one store. In addition, managers must decide on products to place in each store and how much space to allocate to each category at the store level.

**The continuous assortment optimization cycle**

Assortment optimization is never over. Mastering it requires a comprehensive and systematic approach that accounts for evolving customer behavior as well as the financial, operational, and strategic elements of the fundamental assortment decisions (Exhibit 2):

— *Delisting.* Evaluate an SKU's performance along dimensions such as financial and cost performance, customer perception, and strategic importance.

— *Listing.* Assess a new product's expected incremental financial contribution and novelty value for customers.

— *Optimal space allocation.* Base decisions on the amount of available space in each store to allocate to each category (macrospace allocation) and which SKUs to list in which stores (localization) using store-specific factors as well as an understanding of a product's marginal contribution to overall profitability.

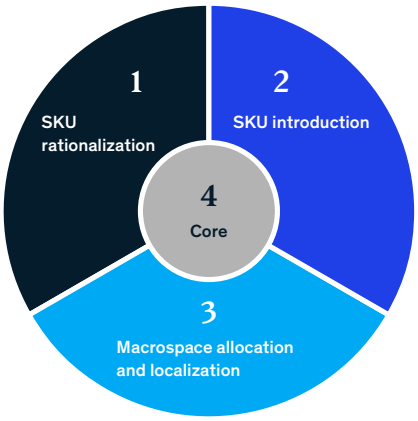
To sustain this analytical process, the organization must have an analytical foundation comprising a sophisticated analytical tool for commercial staff who have adequate analytical skills. In addition, retailers will need to adapt the processes in their commercial organizations to account for the time and interactions required to make use of new insights. For instance, commercial managers might incorporate the results of assortment optimization analysis into supplier negotiations.

**Whether an SKU is listed or delisted should not be based on simple financial measures such as total sales or rotation numbers alone.**

Exhibit 2

## Assortment optimization continuously and automatically assesses the listing, de-listing, and optimal allocation of SKUs.

**Continuous assortment optimization cycle**




**1 SKU rationalization**

Aggregate empiric key performance indicators in a listing index to quantify an SKU's "right to be listed"

What I don't want, but is there...

**2 SKU introduction**

Identify optimal choice of SKUs to list to best meet customer needs

What I want, but is not there yet...

**3 Macrospace allocation and localization**

Determine optimal choice of space per category and SKU allocation at store level

Do I find the right products in my local store?

**4 Core**

Continuous improvement of processes, capabilities, and tools

Will I be able to maintain the process?

## SKU rationalization: Managing multidimensional SKU-performance in the delisting process

Whether an SKU is listed or delisted should not be based on simple financial measures such as total sales or rotation numbers alone. While traditional KPIs are important, other dimensions should help determine the SKU's performance. The complete performance dimensions for an SKU include: economic performance, uniqueness and value to the customer, cost to serve, and role in meeting the retailer's strategic objectives.

— *Economic performance: Total and local financial contribution.* Total product sales in isolation can be misleading because that number depends on how broadly the product was listed, including how many stores carried it and how many weeks it was on the shelf. Granular data points such as sales per week, per store, or per basket give retailers a more useful metric for a product's current and potential total economic performance.

— *Uniqueness: SKU substitutability and value to customers.* Similarly, traditional financial metrics can be misleading indicators of a product's value. Seemingly insignificant products, as measured by sales, for example, can be so important to some customers that these customers would take all of their retail shopping elsewhere if that product became unavailable in a store.

  By applying advanced analytics to the retailer's massive point-of-sale data, we can quantify a product's uniqueness. In fact, McKinsey's proprietary walk rate and transferable demand analytics predict the share of a delisted product's sales that would be reallocated within the category (and to where) as well as the share of its sales that would be lost for the category (see sidebar "Customer decision trees and the roots of product uniqueness").

— *Cost to serve: SKU end-to-end cost.* Because local supply chains can differ, operating costs to keep an SKU on the shelf can vary significantly across stores. A cost-to-serve analysis quantifies logistics costs at the level of both the SKU and the store and reveals end-to-end costs that extend financial considerations beyond gross margin to include operating costs for a fuller view of an SKU's profit contribution.

— *Strategic objectives: Beyond current performance.* Not all retail success is directly or immediately reflected in current financial or operational KPIs. Strategic KPIs can be introduced at the SKU level, enabling retailers to take other objectives into account in their assortment decisions. One strategic objective may be to gain a higher share of organic, gluten-free, or regional products. Another might be to increase the number of SKUs that are appealing to strategically important customer segments such as millennials, wealthy, or middle-class consumers.

There are more than 30 distinct KPIs across these four dimensions. In most cases, two or three dimensions and three to five KPIs are enough to capture the relevant aspects of an SKU's performance. This selection of KPIs can then be summarized in a weighted listing index that yields a ranked list of all SKUs in a category. The ranking offers a convenient starting point for the category manager to decide which SKUs to keep and which to delist (Exhibit 3).

The SKU rationalization process yields the best results when category managers combine science (analytics and KPI rankings) and art (experience and market knowledge from category managers). Therefore, a position in the bottom tier of the listing index does not necessarily require delisting.

## SKU introduction: Systematically assessing listing opportunities

Delisting might reduce systemic assortment complexity or achieve higher average gross margins. Most delisting efforts, however, are also driven by the introduction of new SKUs. These SKU introductions typically fall into one of four categories:

— Extending distribution (listing an SKU in more stores within a retailer's network)
— Introducing a new private-label SKU
— Listing new branded products
— Listing new categories or introducing other offerings

Exhibit 3

## In our advanced analytics–powered, KPI-based ranking approach, each SKU's performance is quantified along up to four key performance dimensions.

### Example KPI for the four performance dimensions

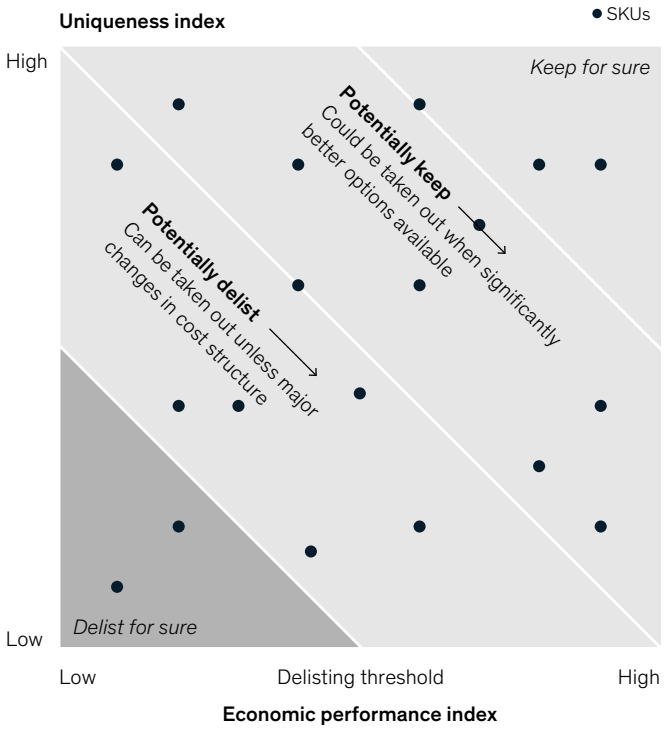
**A Economic performance**
- Total sales per year across whole network
- Sales per week per store: Performance when given shelf space
- Gross margin (including all supplier contributions)
- Basket-leverage: Average size of baskets containing this SKU

**B Uniqueness**
- Walk rate: Share of units that will not reallocate to other SKUs in the category when the product is delisted
- Need-state density: Average number of SKUs per customer switching box the SKU is in

**C Cost to serve**
- End-to-end logistics costs per SKU per store
- Wastage ratio: Share of SKUs thrown away
- Out-of-stock ratio: Share of time when product is out of stock

**D Strategic objectives**
- Binary value for strategically important product attributes (regional, organic, vegetarian or vegan, etc.)
- Outperformance of the product in a strategically important customer group, eg, upper middle class, Generation Y

### Two-dimensional listing-matrix (conceptual)




Category managers can systematically evaluate the viability of these options using an advanced analytics-based approach that assesses the economic effect of an SKU's listing on the assortment's overall profitability.

### Extending distribution

Advanced analytics can help determine if the SKUs that perform well in some stores would be similarly successful in other stores. An initial review of an SKU's sales per week per store (SWS) and its "share of shelf-weeks" as measured by the total listing index (TLI) can uncover hidden champions: SKUs that have very high SWS and low TLI (Exhibit 4).

For some SKUs, a low TLI could be due to not being listed all year, as with seasonal products or SKUs associated with problems in the supply chain. For other SKUs, a low TLI may result from being listed in a small number of stores within the store network.

## Customer decision trees and the roots of product uniqueness

**Customer decision trees (CDTs)** are visualizations of a customer's decision-making process when selecting an SKU. CDTs depict the customer need-states, clusters of products in each category where switching between products will mostly take place. These clusters typically share common attributes. In the example of a CDT for yogurt (exhibit), lactose-free yogurts and yogurts made from soy milk form distinct customer need-states. The hierarchy of attributes, such as price level, brand, taste, texture, and pack size, is important information for the category manager because closely related need-states should be located closer together in the planogram design.

CDTs are also used to simulate customer-switching, as sales of a to-be-delisted SKU will more likely be redistributed to SKUs in nearby need-states. The likelihood of switching from one need-state to another is visually represented by the vertical distance between the two need-states.

Simulating this switching behavior in a transferable demand model, a McKinsey tool, also allows a product's uniqueness to be quantified by calculating its walk rate as the share of units that would not be redistributed to other SKUs in the category.

In the example, most unit sales of a lactose-free yogurt from brand A will be redistributed to other brand A yogurts. A smaller portion will be redistributed to brand B, and a still smaller share will go to soy-milk yogurts. Relatively few SKUs of lactose-free yogurt means fewer alternative SKUs in which to reallocate brand A's lactose-free yogurt sales. For this reason, lactose-free yogurts will have a higher walk rate than an SKU of (mainstream) brand D, for which a customer has many alternatives from the same brand and other mainstream brands.

While a fully labelled CDT can provide rich qualitative insights on customer shopping behavior, category managers sometimes shy away from labeling a category tree of more than 500 SKUs. Identifying the common attributes and interpreting the need-states of such a large category is a significant commitment. The good news is that when the focus is on measures of uniqueness such as walk rate, category managers can skip this step and generate the relevant key performance indicators with an appropriate proprietary—literally—at the push of a button.

Exhibit

### A deeper look at customer purchase behavior can help to quantify a product's uniqueness.

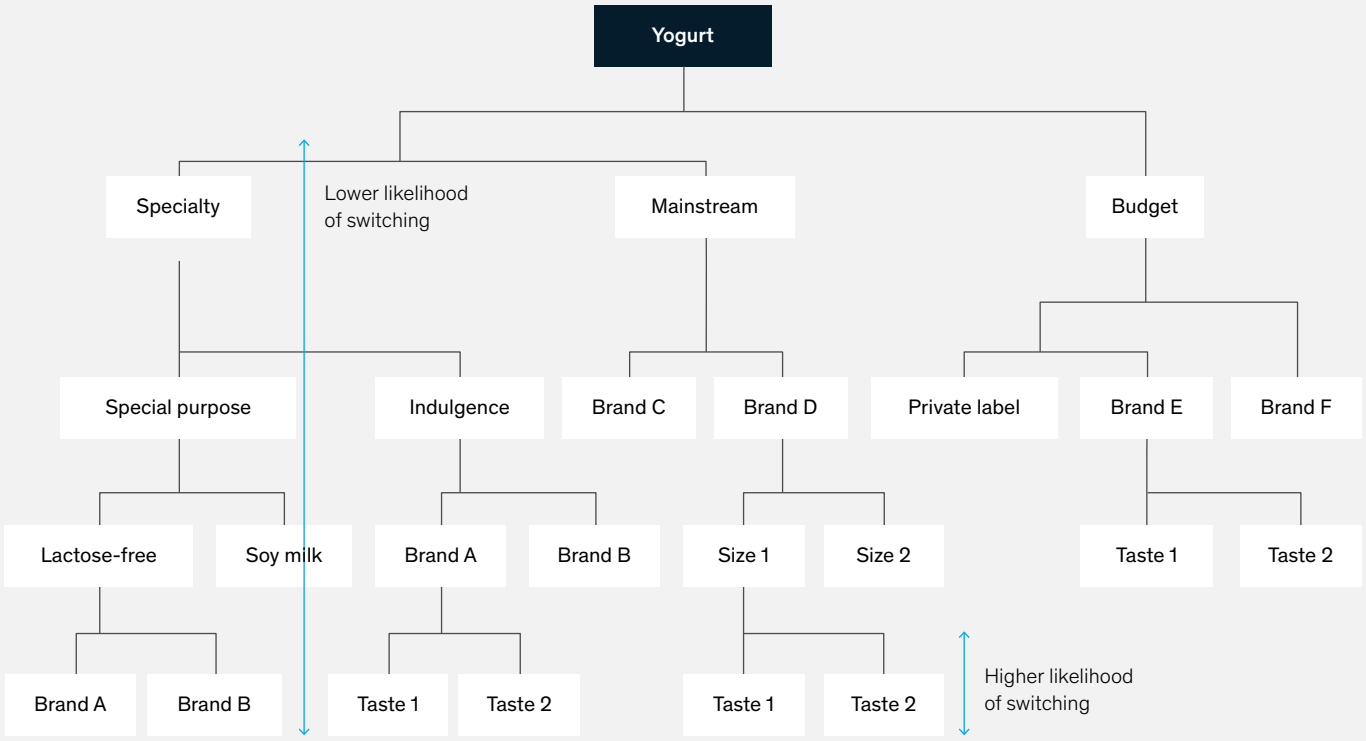
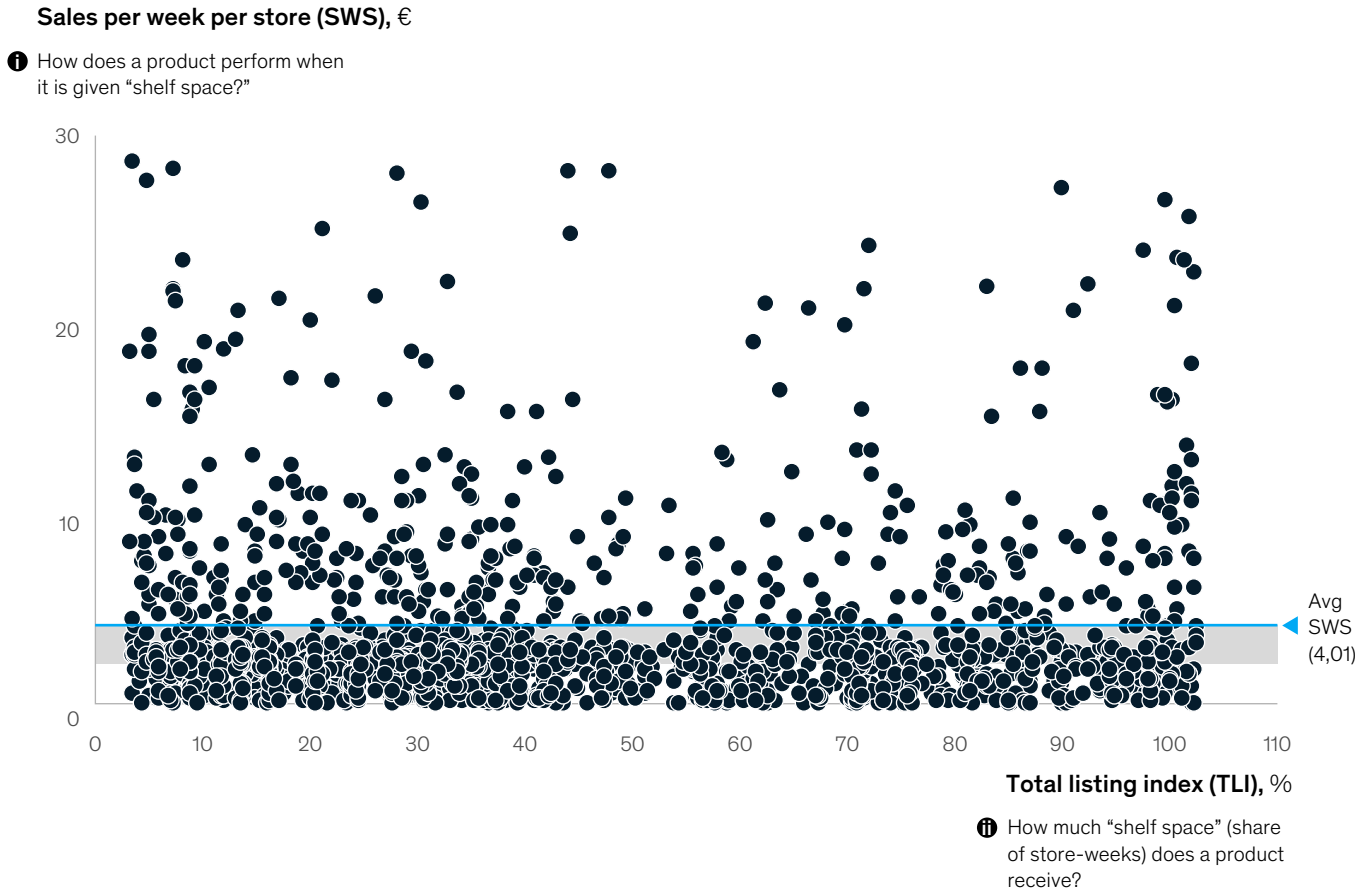


Exhibit 4

## Advanced analytics can identify ‘hidden champion’ SKUs.




Not all local products with high SWSs would perform similarly in a nationwide listing. However, these “local champions” deserve a closer look to ascertain whether distribution extension could turn them into high performers in a larger part of the store network (for the advanced analytical process behind such an assessment, see “Macrospace allocation and localization: Ensuring optimal space allocation in stores”).

### New private-label products

A brand’s national or international success cannot be the primary metric in deciding whether to develop a private-label line that mirrors the characteristics of the existing brand. CDTs reveal the potential upsides of adding a private-label line to a retailer’s assortment by enabling an assessment of private-label penetration in the main need-states (Exhibit 5). Category managers should then prioritize need-states with below-average private-label penetration for new private-label introduction.

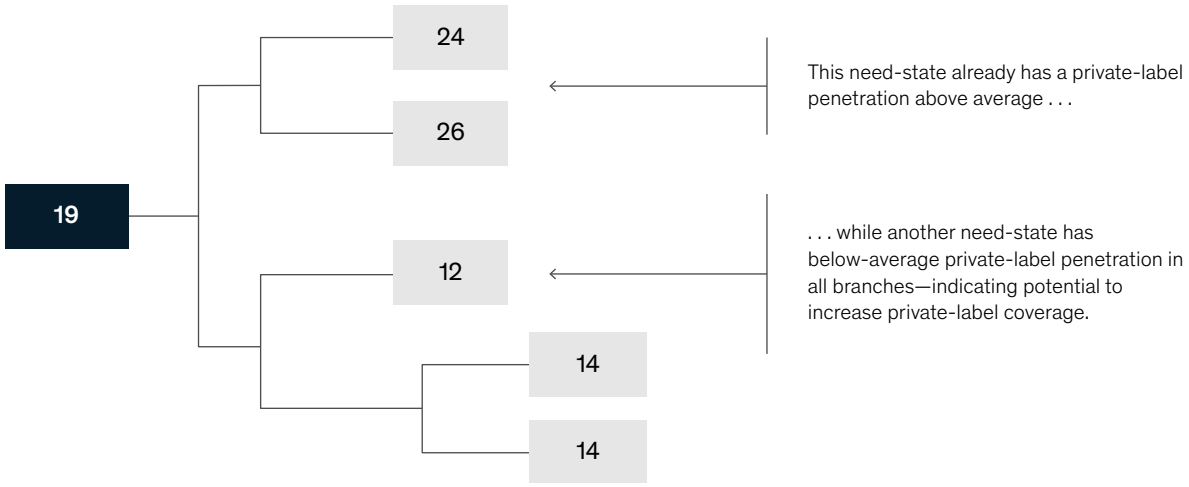
### New branded products

The introduction of new branded products is often supplier driven. However, not all new products offer incremental value and more consumer choice. An advanced analytics-based assessment helps retailers predict the impact of listing a new branded product from a customer point of view (Exhibit 6).

Exhibit 5

## Private-label share by customer need-state.

%


24
26
19
12
14
14
This need-state already has a private-label penetration above average . . .
. . . while another need-state has below-average private-label penetration in all branches—indicating potential to increase private-label coverage.

This assessment can help retailers locate new products in the CDT by comparing their attributes with those SKUs in the current assortment. This comparison can yield important insights about the novelty value of the new SKUs. The CDT could reveal that the new branded product is in a need-state that is currently sparsely served by SKUs. It could even show that the new SKU would be the only product in a need-state that the store is not yet addressing. In this case, the low or nonexistent risk of cannibalization and likelihood of an incremental increase in sales could propel a decision to list the new product.

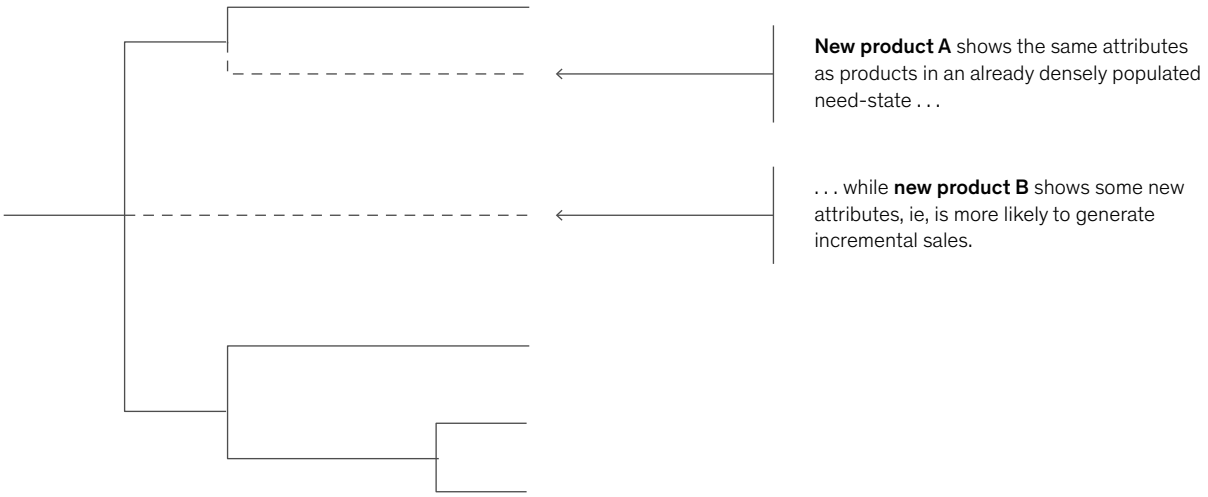
This semiquantitative method to assess the uniqueness of a not-yet-listed product can be part of a systematic listing process in which the category manager begins by collecting an initial number of potential SKUs to list. This list could be populated from sources such as supplier proposals, market information (such as national top 100 lists for each category), and competitor store checks. The candidates on the initial list would then be assessed based on their uniqueness as well as expected sales and margin.

### New offerings

To compete both online and offline, retailers are constantly scouting innovations in their store offerings and increasingly considering new category or service offerings. Innovations can include increasing the selection of organic products in their fresh departments or adding a tasting bar to the ready-made food section. Here, the marginal profit contribution per category is fundamental. Incremental profit from, for example, the next meter of shelf space within a category is estimated using a "reverse transferable demand" model (see earlier discussion on CDTs). In this case, however, the model is used to predict from which listed products in the category the new SKUs would draw sales. It would also determine which of their sales would provide true additional sales to the category, information used to determine which categories to cut shelf space from to make room for a new category or offering.

Exhibit 6

## Need-state density: Number of SKUs per switching box.


**New product A** shows the same attributes as products in an already densely populated need-state . . .
. . . while **new product B** shows some new attributes, ie, is more likely to generate incremental sales.

## Macrospace allocation and localization: Ensuring optimal space allocation in stores

Because stores differ in size, traffic connection, and neighborhood sociodemographic characteristics, not all products will perform equally well across stores. Therefore, it is important to have a flexible approach to determining how much store space to dedicate to which category (macrospace allocation) and which SKUs to list in which store (localization). Category managers can approach macrospace allocation and localization using different levels of sophistication and regional differentiation.

In a basic model, space per store can be allocated across categories using the concept of "marginal profit contribution per category" described above: how much additional margin would an added meter of shelf space yield for a category? Space allocation across categories is then performed in an optimization process using the trade-off between different categories' marginal profit contribution per additional meter of shelf space as a key metric.

Focusing on localization provides a more sophisticated method to assess the optimal allocation of SKUs to individual stores. We first determine which among a large set of microlocation factors best predict a category's economic performance. We then build store clusters using similar microlocation factors and assess which well-performing SKUs in a smaller store cluster could be extended to the entire cluster or network.

Simultaneously optimizing macrospace allocation and localization allows for highly sophisticated recommendations on store-specific, SKU-level space allocation.

# 3 The core: Laying the organizational foundation

**It's worth repeating** that assortment optimization is never finished. It is a continuous process where each listing opportunity triggers a delisting process and yields insight on where to list the new SKU. It is therefore important that the organization is equipped to manage this process on an ongoing basis.

An organization must develop three dimensions to fully capture the value of advanced analytics: culture and processes, skills, and analytics tools.

## Cultivate a culture and adapt processes around analytics

Rich analytics-derived insights will never reach their full impact if decision makers don't use them. All processes along the assortment optimization cycle must be reviewed and redesigned in-line with an organization-wide belief in and commitment to analytics as the most logical driver of major decisions.

Of course, an analytics orientation does not mean that the domain knowledge of experienced retail professionals is unimportant. To the contrary, an organization that can combine analytics with the commercial organization's experience is more likely to reap significant financial and strategic benefits from, for example, supplier negotiations informed by analytics.

## Bring skills in line with the new approach

An analytics-informed assortment strategy also requires technical skills from commercial staff to make most of the deployed tools. These skills include the ability to operate the tools effectively and translate analytical insights into actionable recommendations for the business.

Building the functional skills related to analytics is essential to understanding and drawing connections between data and then translating those insights into action. Such skill-building is as institutional as it is individual. Analytical skills should not be the domain of a handful of people in a siloed insights division but must be deeply integrated into retailers' commercial operations.

**An organization must develop three dimensions to fully capture the value of advanced analytics: culture and processes, skills, and analytics tools.**

## Deploy the right tools

Many tools for assortment analytics exist, but not every retailer needs every available tool. A tool with a broad set of difficult-to-use features, many of which may not be relevant to a retailer's needs, is not a useful tool. In fact, a fully loaded enterprise tool might not only be an unwise and unnecessarily costly investment, it could also cause frustration that can sour an organization against advanced analytics, which would ultimately cost a retailer even more.

We encourage an alternative approach to tool selection that involves starting the journey with simple but appropriate tools and adapting them with new features only as necessary. This approach minimizes the up-front investment and leads to faster returns (Exhibit 7).

The tool in its final and optimal configuration can then be operated as software as a service (SAAS) or transferred to the internal IT or business intelligence team to ensure full organizational autonomy.

Exhibit 7

### To ensure both effectivess and user friendliness, we start with a basic tool and configure it according to emerging requirements.

**Standard approach**

**Install typical standard tool**

Aspiration to create one-size-fits-all

Tool dictates process

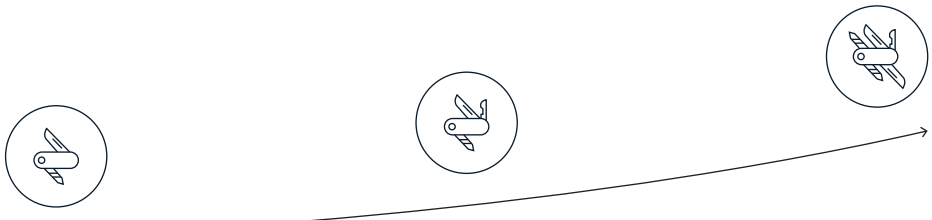
Organization is swamped with number of functionalities

Too many functionalities reduce usability

**Our iterative approach**

**Start with a base model that contains key features required to drive insights and impact**

**Then add tested, new features as you go along**



Start with a prebuilt, highly effective base model, to develop proof of concept and initiate transformation

While working with the base version, identify the further requirements for tool extension (involving end users)

Potentially migrate to more elaborate tool when requirements are clear and capabilities are built

# 4 Getting started

**The assortment optimization cycle** involves delisting, listing, and macrospace allocation and localization, but not all parts are always equally important to all retailers. To meet each organization's specific needs, we've developed a modular approach to assortment optimization that consists of three main elements, plus an initial assessment to analyze overall assortment performance and prioritize areas of improvement. We also address the transfer phase required to ensure that the core of the initiative is integrated as part of the institution.

McKinsey supports laying a foundation for assortment excellence in three phases:

**Proof of concept**
The first phase is led by McKinsey and lasts one to three months. After a one-time data transfer from client IT to McKinsey's advanced analytics engine, the team focuses on commercial insights for an initial three to five categories. Meanwhile, McKinsey begins to map the client's commercial processes and identifies opportunities for improvement. In parallel, category managers will begin to develop analytical skills by working alongside McKinsey in the project.

Quick wins are usually identified in this phase, which can yield prompt returns that make the whole assortment optimization journey self-funding.

**Rollout**
The second phase is coled by McKinsey and the client and spans the next three to six months. Insights from phase one inform the configuration of the analytics tool, which is then applied to all product categories and typically accessed in a SAAS model. Joint ownership of this phase helps the organization align commercial processes with analytics and engage in large-scale skill-building. In this phase, all assortment opportunities are evaluated and systematically assessed, which includes identifying more quick wins.

**Institutionalization**
The final phase makes sure the impact is lasting. This phase puts the client in the lead and ensures that analytics-driven assortment optimization is woven into the fabric of the organization. Analytics tools tailored to the organization's needs, category managers who have gained analytical expertise, ongoing process checks, and continuous analytics skill-building will help ensure that the changes last.

After going through these three phases, retailers are fully equipped to take on the next iterations of the assortment optimization cycle and can begin reaping the benefits of higher margins, lower costs, increased sales, and higher customer satisfaction. ■

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